

## CLIMATE CHANGE AT LOCAL LEVEL: COPING WITH UNCERTAINTY

Ray McGrath, Steffi Gleixner, Tido Semmler (Met Éireann)

### Abstract

All climate forecasts suffer from a degree of uncertainty that is difficult to quantify. The uncertainty is compounded when the basic output from climate models is used to drive ‘practical’ applications that provide guidance for spatial planning programmes. It is essential that predictions delivered to planners adequately reflect the full range of uncertainty associated with the models. This study focuses on the uncertainty in the predictions of future river runoff in 9 catchment areas; it extends an earlier study that addressed only the errors in the hydrological model, not the climate model. The new study uses the latest climate data from 13 independent regional climate model simulations provided by the ENSEMBLES<sup>1</sup> project to reassess the predicted changes in river runoff associated with climate change.

### 1 Introduction

The climate system, including our weather, is inherently chaotic. The future is modelled by advancing an initial picture (“state”) of the system (atmosphere, ocean, surface features), in small time steps, in a way that is consistent with well established physical laws. However, tiny changes to the initial state have a profound impact on the evolving forecast (the “butterfly effect” – see Lorenz, 1963); two forecasts launched from initial states that differ only minutely eventually produce radically different results. This is a fundamental feature of chaotic systems: regardless of the model accuracy, or the available computer power, chaos eventually destroys the deterministic ability of the models. Accurate weather forecast for a month ahead, for example, will never be feasible due to chaos. Climate modelling partially overcomes this limitation by enquiring only about the *average* weather; details about *specific* years or seasons or days are sacrificed in the investigation of climate change.

The physical models that form the basis of climate predictions are also deficient both in their ability to represent the full range of climate-related processes and spatial details. Ongoing research is gradually improving the realism of the models but the huge computational cost of running advanced models imposes its own limitations. Matching computer power with the aspirations of the modellers usually results in a compromise on the horizontal resolution – the scale of spatial detail picked out by the model; with today’s supercomputers this is typically set in the range 150-300 km<sup>2</sup>. For weather parameters such as rainfall this is a serious obstacle to directly using the data in applications as the surface features often have a significant influence on local weather. The surface elevations “seen” by the model, for example, are smoothed average values that are representative of an area specified by the model resolution. The information gap can be partially addressed by using statistical or dynamical downscaling methods but at a cost of introducing further errors.

Even with perfect, non chaotic, models the uncertainty cannot be eliminated from climate predictions as the extent of climate change is directly linked to current and future emissions of Greenhouse Gases (GHG); future emissions are subject to considerable uncertainty. This additional uncertainty becomes more relevant in climate predictions for the second half of the century.

Finally, the application models (hydrological, storm surge, etc.) introduce their own errors. Unfortunately, the cascade of uncertainty may not be a linear process; the errors may be greatly amplified by sensitivity to the driving weather elements.

---

<sup>1</sup> See <http://ensembles-eu.metoffice.com/index.html> for details concerning this EU project.

<sup>2</sup> Met Éireann plans to run the new EC-EARTH global model at horizontal resolutions ~50 km in 2009, but only for simulations extending a few decades.

It is essential that predictions delivered to planners provide adequate estimates of the total error. An ensemble model approach is typically used to map the model uncertainty; many simulations are run with slight changes to important model parameters and the “spread” in the results is used as a measure of the uncertainty. In the case of the climate model, the simulations must also reflect uncertainty in GHG emissions. However, the method is not without its problems. There is no guarantee, for example, that the full spectrum of possible solutions is being sampled, or that the sampling is unbiased (i.e. the mean of the simulations may not converge to the true solution). Nevertheless, experience with this approach in day-to-day weather forecasting does suggest that the method has significant merit.

**2 Modelling river discharge**

An earlier study (Dunne et al., 2008; Mc Grath et al., 2008) provided predictions of future river flow in 9 catchment areas using meteorological data from a single climate model simulation to drive the HBV–light hydrological model. The work is here revisited following the availability of a dozen more climate datasets – regional climate model simulations - based on different models and future GHG scenarios.

The nine catchments (Bandon, Barrow, Blackwater, Boyne, Brosna, Feale, Moy, Suck and Suir) are shown in Figure 1. The ensemble simulations cover the periods 1961-2000 (reference) and 2021-2060.

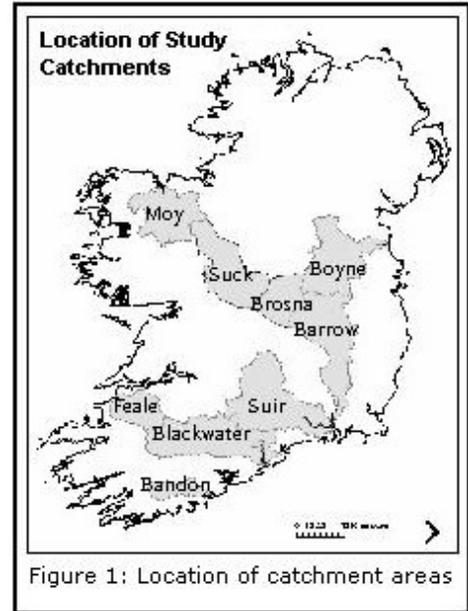


Figure 1: Location of catchment areas

**2.1 Method**

Full details of the method can be found in the original study. Briefly, the river flow was simulated using the rainfall runoff model HBV-light, driven by daily precipitation and temperature data supplied by the regional climate model simulations. These simulations are listed in table 1.

Data for the future period with the C4I simulations data were only available for the A2 and B1 GHG scenario forcing; for these simulations the reference A1B scenario was taken as the reference.

Institute	Model	Driving GCM	Scenario	Resolution
C4I	RCA3	ECHAM5	A1B	13-14km
C4I	RCA3	ECHAM5	A2	13-14km
C4I	RCA3	ECHAM5	B1	13-14km
C4I	RCA3	HadCM3 high sensitivity	A1B	13-14km
C4I	RCA3	HadCM3 low sensitivity	A1B	13-14km
C4I	RCA3	ECHAM5	A1B	25km
C4I	RCA3	HadCM3 high sensitivity	A1B	25km
ETHZ	CLM	HadCM3Q0	A1B	25km
KNMI	RCAMO	ECHAM5	A1B	25km
METNO	HIRHAM	BCM	A1B	25km
MPI	REMO	ECHAM5	A1B	25km
OURANOS	CRCM	CGCM3	A1B	25km
SMHI	RCA	ECHAM5	A1B	50km

**Table 1:** List of climate simulations used to simulate river runoff. For details concerning the models and institutes see the ENSEMBLES web site: <http://ensembles-eu.metoffice.com/index.html>.

With the exception of the simulations from METNO, ETHZ and OURANOS (simulations out to 2050 only), the ensembles provide daily precipitation and temperature data over the two 40-year periods. The data were interpolated to the locations of several meteorological stations within the catchment area and a weighted mean calculated.

## 2.2 Bias correction

Most of the simulations show a systematic bias in the precipitation data when compared against observations in the reference period. A correction method (see original study) was used to ensure good agreement with the number of dry days and also to correct for bias in the wet days. In general this produces realistic simulated precipitation that closely tracks observed values. A difficulty with the method is that for most catchments the closest synoptic station that is used to fix the bias is outside the area. The problem is highlighted in the Blackwater and Feale catchments when using the MPI climate simulations. An example is shown in Figure 2 for the Feale catchment. The left plot shows that the mean daily precipitation for the 7 meteorological stations (grey lines) is overestimated compared to the observed precipitation at the closest synoptic station (dashed black line). However, since the simulated precipitation at this synoptic station (black line) is distinctly higher than at the meteorological stations, the bias correction calculated with the data at this reference station corrects the precipitation within the catchment to values considerably lower than the observed data (right plot in Figure 2).

## 2.3 Uncertainty in the Hydrological Model

The HBV-light model is highly tunable with a large number of parameters. Previous experiments using a Monte-Carlo approach identified the 100 best parameter sets. These same sets were used in this study.

### 2.3.1 Validation of the model

For most simulations and catchments the monthly mean of the simulated stream flow over the 40 years of the reference period shows good agreement with the observed stream flow.

Figure 3, for example, shows the results from using the C4I simulation (13-14 km grid) driven by the HadCM3 'high sensitivity' global climate model. For the most part the observed stream flow (solid black line) lies within the range of the 100 HBV-light simulations (grey lines) based on parameter variation. The mean of the parameter set (dashed black line) shows the same annual cycle as the observations with a minimum in summer and a strong maximum in winter.

Results based on using the other climate model simulations are broadly similar. Figure 4 gives an overview of the results when the 13 climate simulations are used to drive the 100 HBV-light ensemble; for ease of interpretation only the mean values of the parameter sets are shown together with the observed stream flow (solid black line).

Agreement between models and observations is quite reasonable, except for the Blackwater and Feale catchments – probably a reflection of deficiencies in the precipitation bias correction method. While the corrected MPI climate model precipitation data are, as already mentioned, too low, leading to lower than observed stream flow, the METNO model data are biased in the opposite direction.

### 2.3.2 Extreme values

The monthly extreme values, averaged over the 40 years and for the 1300 simulations (13 climate model simulations, 100 HBV-light parameter set) are displayed in Figure 5 as dashed lines together with the mean extreme values of the observed stream flow (solid lines). Except for the Feale, there is good agreement between models and observations, particularly in the summer.

### 2.4 Future predictions

The percentage change in the river run-off between the reference and future time periods is shown in Figure 6. The 1300 simulations (grey lines; mean is indicated by the solid black line) give a measure of the uncertainty in the predictions – uncertainty both from the climate models and the HBV-light model.

Catchment	Decrease in summer	Increase in winter
Bandon	99.37%	84.66%
Barrow	96.56%	89.74%
Blackwater	97.77%	86.15%
Boyne	93.87%	89.90%
Brosna	97.44%	87.87%
Feale	98.51%	70.82%
Moy	96.77%	82.67%
Suck	98.73%	84.59%
Suir	98.54%	89.74%

**Table 2:** Percentage of the 1300 simulations with the indicated trend.

The results are consistent with the original study, showing a general increase in winter (~10%) and a strongly marked decrease (~30%) in summer (see Table 2 for significance). For clarity, the mean data are shown in Figure 7. With the exception of the results for the Moy catchment in June, all simulations agree on the decreasing stream flow in summer. The highest reductions can be observed in the of Bandon, Suck and Suir catchments, where some simulations show a decrease of up to 50% in the run-off.

Comparing the change in the river run-off with the change in precipitation suggests a strong temperature influence. Figure 8 displays the mean daily difference in precipitation between the two selected time periods for all regional climate models. In winter both the stream flow (Figure 7) and precipitation amounts (Figure 8) increase by 10-15% on average. In summer the decrease in the stream-flow averages 20-30% and is much stronger than the precipitation change, which ranges around minus 10%. The difference is due to the increasing temperatures and the related increase in evaporation.

#### 2.4.1 Extreme values

The changes in the average of the extreme values are shown in Figure 9. Note that in summer, with the exception of the Feale catchment, the frequencies of the lowest flows show a higher decrease compared with the corresponding figures for the largest flows. In winter the signal is reversed. For completeness Figure 10 shows the actual highest/lowest simulated stream flows.

#### 2.5 Impact of new climate model ensembles

It is instructive to compare the results based on 1 climate simulation (Figure 11 – taken from the original paper by Dunne *et al.*) with the revised projections based on the 13 climate simulations (Figure 6). With the new data the strength of the annual cycle is reduced and the summer flow reduction in particular is less pronounced (40-50% reduced to 20-30%).

### 3 Conclusions

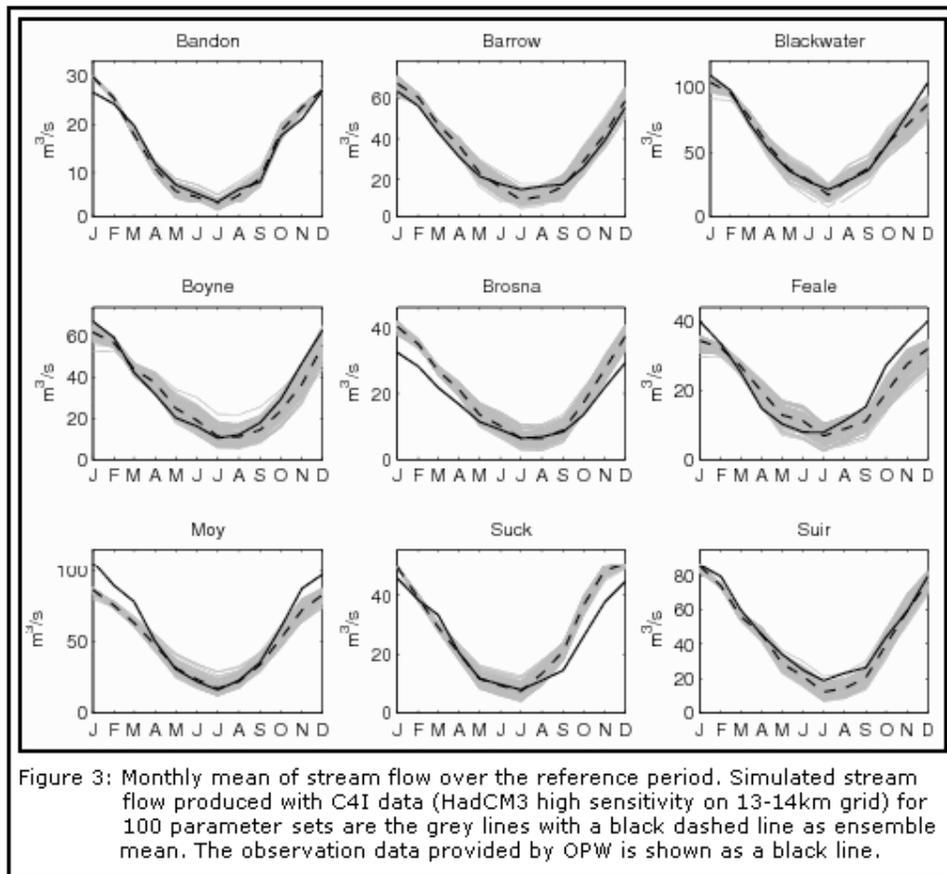
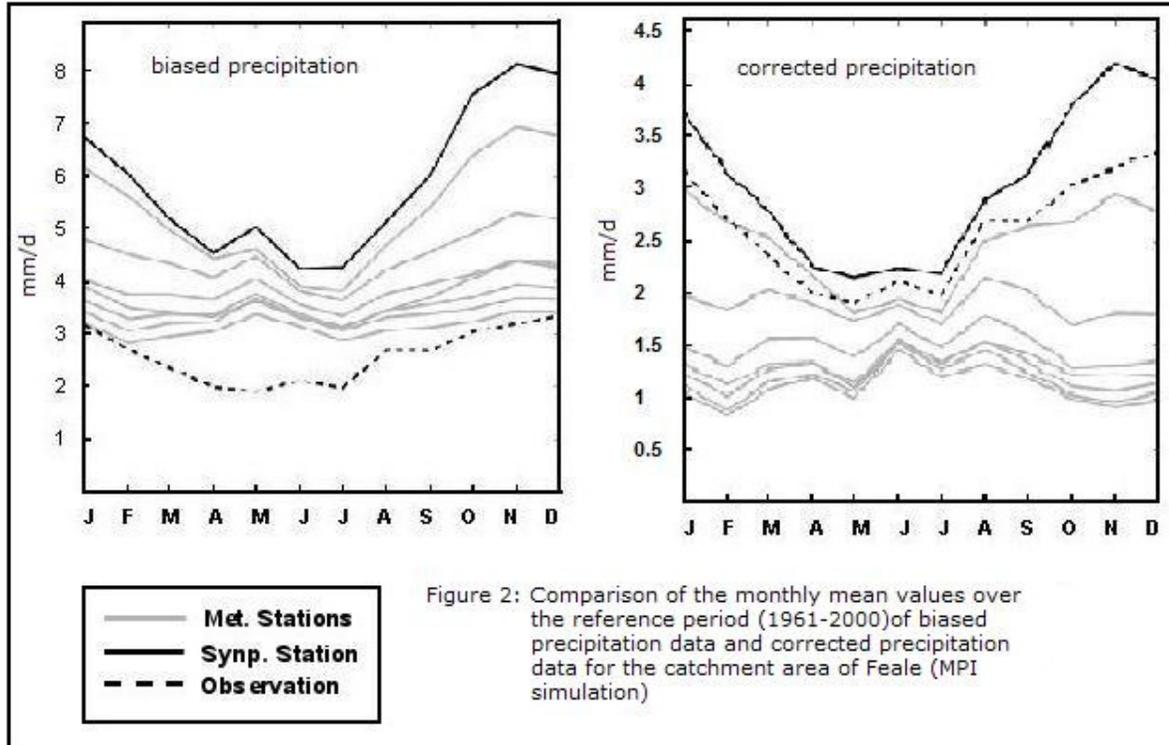
Spatial planning programmes that require guidance on climate change need accurate estimates of the full uncertainty associated with climate application predictions. Estimates of future river runoff, for example, will be subject to errors in both the hydrological model and the climate model used to provide the driving data. In this study the impact of the climate model error is assessed by extending a previous river runoff study to include the latest available regional climate model datasets (13 model simulations). The study broadly confirms the results of the previous study (reduction in future summer flows, increase in winter flows) but the uncertainty in the climate predictions, reflected in the spread of the 13 simulations, has the effect of attenuating the strong annual signal of relative change shown in the earlier study. The reduction in summer flow is also less pronounced. The importance of temperature in the warming climate is also highlighted as a strong influence on future summer river flows.

#### Acknowledgements

The catchment study was funded by OPW and primarily carried out by Steffi Gleixner, a visiting student. The graphs and tables are taken from her report.

#### References

- Dunne, S., Lynch, P., McGrath, R., Semmler, T., Wang, S., Hanafin, J. and P. Nolan, 2008: The impacts of climate change on hydrology in Ireland. *Journal of Hydrology*, DOI:10.1016/j.hydrol.2008.03.025
- Lorenz, E. N., 1963: Deterministic nonperiodic flow. *Journal of Atmospheric Sciences*. Vol. 20: 130-141.
- Mc Grath, R., Lynch, P., Dunne, S., Hanafin, J., Nishimura, E., Nolan, P., Venkata, R. J., Semmler, T., Varghese, S. and S. Wang, 2008: Ireland in a warmer world: scientific predictions of the Irish climate in the twenty-first century. (Available from Met Éireann.)
- OPW, 2007. Hydro-Data website (<http://www.opw.ie/hydro/>)
- Seibert, J., 2005: HBV light version 2 User's manual, Stockholm University – available at [http://people.su.se/~jseib/HBV/HBV\\_manual\\_2005.pdf](http://people.su.se/~jseib/HBV/HBV_manual_2005.pdf)



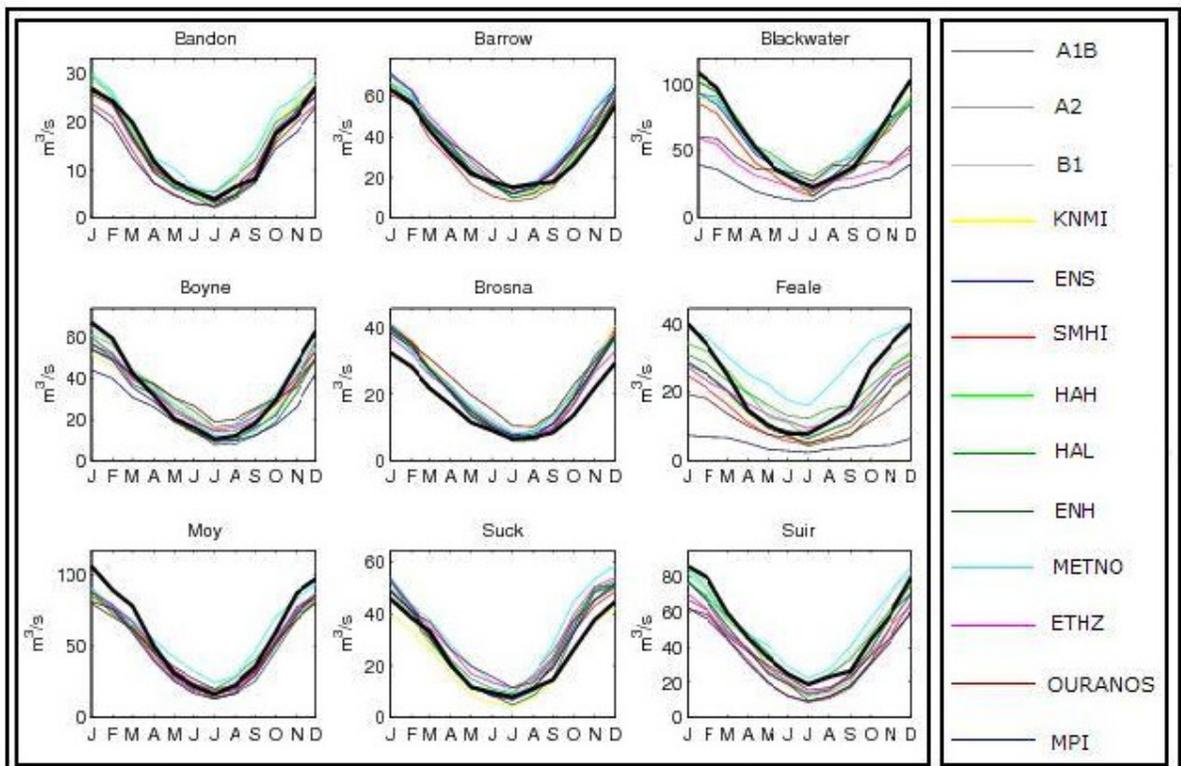


Figure 4: Monthly mean of stream flow over the reference period. Colored lines are the means of the parameter sets for the 13 different input datasets. The black line is the observation data.

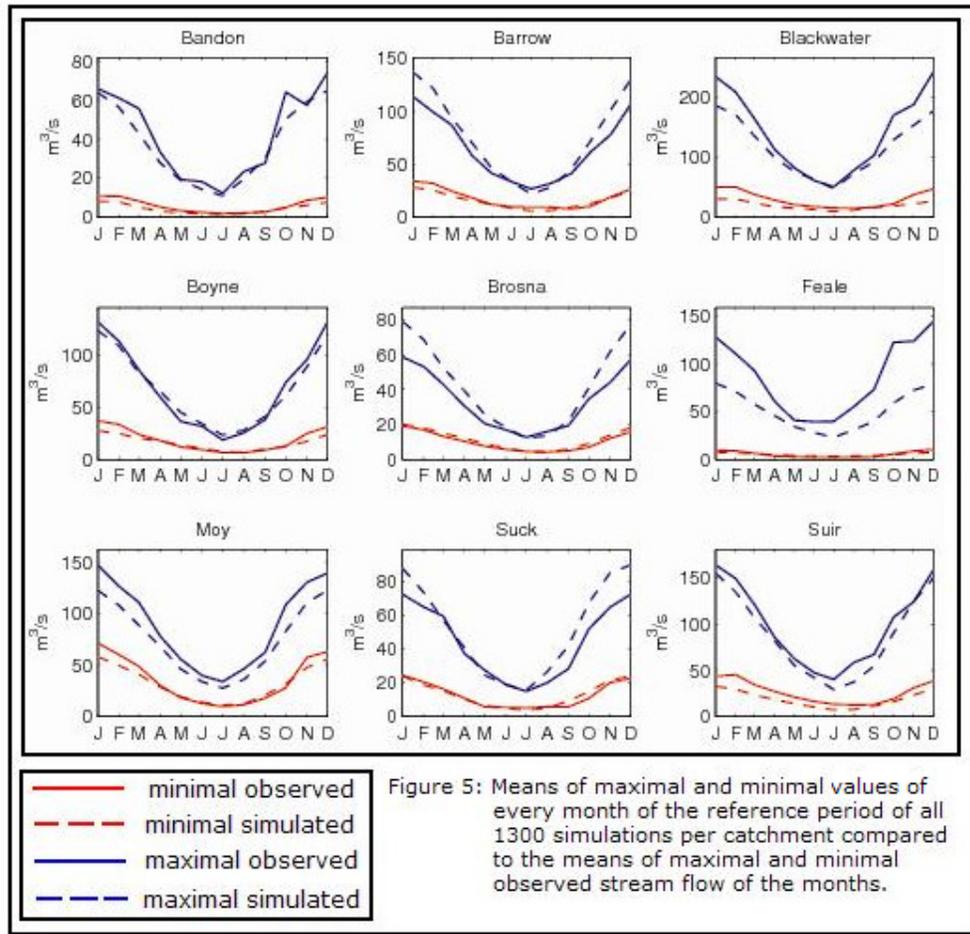


Figure 5: Means of maximal and minimal values of every month of the reference period of all 1300 simulations per catchment compared to the means of maximal and minimal observed stream flow of the months.

